Wireless Identification and Classification of Arrhythmias on Portable ECG Using ANN Method

Emilliano, Nendi Suhendi Syafei, Peri Turnip, Gilbert F. Yohanes, Giraldo P. Jeremy, Nguyen Le Hoa, and Arjon Turnip

***Abstract*— Heart disease, especially Arrhythmia cannot be seen directly because there are no symptoms, and can only be known by carrying out an examination by a medical expert or using an electrocardiograph (ECG). Most current ECG devices cannot perform classification directly. For this purpose, a classification system that has high accuracy is needed so that the results of the analysis can be credible. The Artificial Neural Network method is one of the methods offered because it is suitable for dealing with complex classification problems. In this study, a classification model will be created based on heart wave parameters for Arrhythmia detection. The results of the classification model made have an accuracy of 94.12%. The developed model can help the process of classifying heart disease which is difficult to diagnose.**

***Index Terms*—Wireless, Networking, ECG, Arrhythmia, Classification, ANN.**

I. Introduction

EVERY year more than 36 million people die from Non-Communicable Diseases (NCD). There are more than 9 million deaths caused by non-communicable diseases occurring before the age of 60 [1]. Globally, the number one cause of death for NCD every year is cardiovascular disease. Research shows that heart disease in Indonesia is still the number one disease that has the highest prevalence compared to other diseases [2]. It can be seen from the increase in the mortality rate for non-communicable diseases in 2018 heart disease share accounted for 17.9 million deaths [3]. The large number of deaths is caused, among other things, because the signs of this disease cannot be seen directly, but by carrying out an examination using an electrocardiograph [4]. One of the heart defects that have no symptoms and can be life-threatening is Arrhythmia [5].

Along with the times, there are many ways to find out how to process existing ECG signals [6]. With the help of an ECG device, existing sensors will detect electrical activity in the heart to record electrical changes in the heart and the results can be shown via a graph [7][8]. In the ECG signal wave, commonly waves feature known as PR, QRS, and ST waves [9]. The PQRST wave has each meaning for the type of heart recording signal. Based on the generated signal, it can later be analyzed by experts who can interpret the wave signal [10]. The type and labeling of features extracted from ECG signals has a very important role in classification for the purpose of diagnosing heart disease. Meanwhile, the purpose of feature extraction itself is to find the information content of heart conditions from non-stationary ECG signals so that abnormality detection and prognosis can be carried out efficiently. Various techniques have been applied both for feature extraction and for ECG signal classification, such as artificial intelligence, machine learning, genetic algorithms, and others. One of the feature detection algorithms in the form of QRS was first discovered by Pan and Tomkins in 1985 [11]. The QRS detection is processed in the time domain based on analysis of the slope, amplitude and width of the QRS complex.

Most of the current ECG devices are imported products and have very expensive prices. In addition, the use of ECG devices is impractical because they are less mobile and are usually only owned by large hospitals [12]. For this need, several researchers have created a heart rate monitoring system that uses three lead electrodes based on real-time signal processing so that it can be applied easily [13][14].

The ECG portable - wireless will be integrated using a microcontroller device for the signal filtering process for wave readings and integrated via the cloud or website with the help of the internet [15][16]. There have been quite a few that have provided heart rate recordings for monitoring, but the provision of classification is still not significant. So the authors propose to create a classification model that can be used to identify abnormalities in heart disease to be displayed in the diagnostic results using the ANN method.

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II. METHODOLOGY

The method used is a quantitative method. The dataset to be processed can be taken directly from several experiments that have been carried out previously and by using the MIT-BH dataset from the PhysioNet website. The main data collection will use a portable ECG tool that was made in previous studies using 3 electrodes and then take a recording of heart waves or signals [17][18].

There are approximately 20 subjects involved for the experiment, which were recorded after went through 3 simple tasks as the condition for the data acquisition. All of them filled the Letter of Approval as the recording started and were given a few instructions as per said for the experiment. The position of electrodes that we used can be seen in the Fig. 5, where it's one of the basic lead position for the ECG tool. The placement of the electrodes is the red node on the right chest, the yellow node on the left chest, and the green node on the upper right abdomen. To get the best wave readings you can place electrodes on the chest that are the same distance from the heart (not on certain limbs).

The sensor used in the ECG signal acquisition is the AD8232 module. This component functions to capture electrical signals contained in the cells of a person's body. This module uses 3 electrodes attached, where each electrode has its own role, from positive, negative and neutral electrodes. Each electrode has adhesive so it doesn't fall off when pasted and gel from silicon. The use of gel is intended to increase the signal retrieval conductivity.

The ECG device is equipped with a Bluetooth module to transmit recorded data from the device to the hardware used to process the raw signal. For the conclusion, we used the data from a dozen of experiment's subjects that have been carried out previously using our self-made portable ECG devices to collect the signals for normal dataset signal, and as for arrhythmias signal data from physiobank, then we processed the data using some functions such as baseline correction and filtered it, then we made the classification model out of it using python and tensor flow framework to get the results.

A. *Pre-processing*

The ECG input data obtained will be converted based on the type of data used for signal processing in the form of array to data frame. The converted data will be transferred from the ADC amplitude to the millivolt amplitude. After that, a base-line correction will be made, which functions to separate the actual spectroscopic signal from interference effects or eliminate unnecessary interference effects. Then the data will be filtered using a Butterworth filter using Python-based programming. Then a comparison using FIR signal that is One of the digital which is a filter that can provide efficient calculations in estimating the state of the process by minimizing the noise contained in the ECG signal and being able to separate between the ECG signal and the noise signal is made.

B. *Feature Extraction*

The PQRST contains information value on the heart's electrical potential that can be used to identify several types of possible abnormalities. The PR interval is measured from the length of the P wave to the start of the QRS complex, which is usually 120-200 ms long. The QRS complex is the combination of three of the graphical deflections seen on a typical electrocardiogram. It is usually the central and most visually obvious part of the tracing. It corresponds to the depolarization of the right and left ventricles of the heart and contraction of the large ventricular muscles. The ST segment represents the ventricular repolarization. QT interval represents the duration of ventricular electrical systole, which includes ventricular activation and recovery. The extraction results are the heart rate, RR intervals, PR intervals, QRS width, ST interval, and QT intervals in each of subjects [19]. The RR interval is the intervals between successive heartbeats [20].

C. *Classification*

For the classification method that has been made using ANN with the architecture model given in Fig. 1. The ANN algorithm itself is a sequential or training model based on the neural network of the human brain [21]. By carrying out the learning process independently, artificial neural networks can learn the input given to produce a consistent response [22][23]. Artificial neural networks are designed and trained to have human-like capabilities. The ANN method used will have several layers to adjust the learning weights that will be used in making the model, as can be seen in Figure 6. From the learning results obtained, the test results will be validated with several metrics such as accuracy, precision, recall, and F-1 score [26]-[30].

The model used is feed-forward propagation, and as for the mathematic model can be seen on equation(1). Take a sample having features as X1, X2, and these features will be operated over a set of processes to predict the a diagnosis as an output. Each feature is associated with a weight, where X1, X2 as features and W1, W2 as weights. These are served as input to a neuron. A neuron performs both functions: (i) Summation, (ii) Activation. In the summation, all features are multiplied by their weights and bias are summed up as represented in the equation (1) [31][32]:

$$Y_i = B_i + \sum_{j=1}^{n} X_j * K_{ij} \ , \ i = 1 \dots d \qquad (1)$$

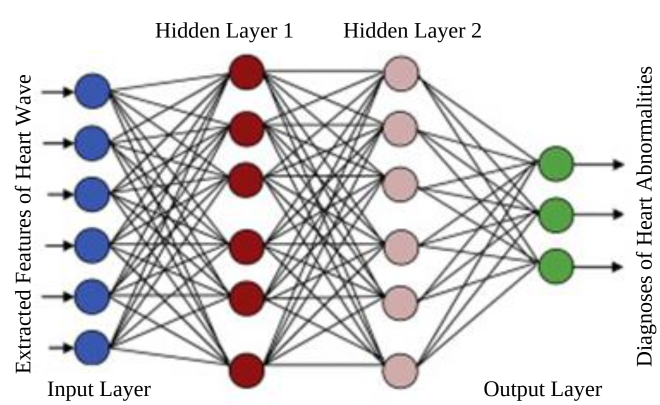

Fig. 1. Architecture of ANN Model

This summed function is applied over an Activation function.

The output from this neuron is multiplied with the weight W and supplied as input to the output layer. The same process happens in each neuron, but the activation functions in hidden layer neurons using ReLU and sigmoid are varying. The main purpose of the activation function is to convert the weighted sum of input signals of a neuron into the output signal. And this output signal is served as input to the next layer.

D. Performance Evaluation

The performance evaluation that is used in this study is confusion matrix. The confusion matrix consists the amount of right and incorrect guesses is the key to the confusion matrix, which is summarized using count values and broken down by class. This matrixes used to verify the accuracy and performance based on some parameters like accuracy, precision, recall, and F-1 scores, confusion matrix. These are the evaluation matrices based on which our performance evaluation exercise has been performed [28]

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

The precision value shows how consistent the model classification results are [28]

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

The recall is the value obtained from the correct prediction by the model which is also known as the probability of detection [28]

$$Recall = \frac{T}{TP+FN} \quad (4)$$

The F-1 score gives the combined idea about precision and Recall metrics [28]

$$F-1\ score = 2\ X\ \frac{Precision\ x\ Recall}{Precision+Recall} \quad (5)$$

Overall the schematic diagram of proposed method including experiment and networking application is shown in the Fig. 2.

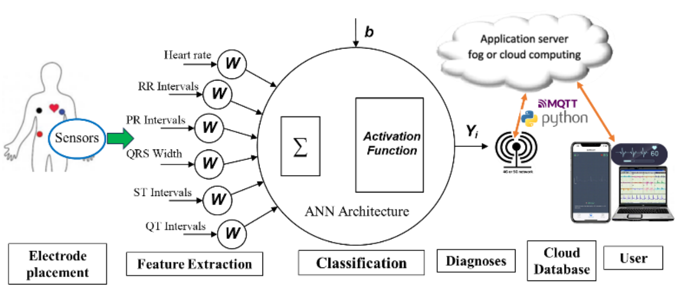

Fig. 2. Schematic Diagram with Experiment Scenario and Networking Application.

III. RESULT AND DISCUSSION

The quality of raw data signal recording using the portable ECG device is as shown on Fig. 3. It can be seen that the recorded data is quite good, there is a little noise. However, to improve the quality of feature extraction, the raw data still needs to be filtered. In the preprocessing, Butterworth filter using Python-based programming was applied. Next, a comparison using the FIR signal is a digital filter that can provide efficient calculations in estimating the state of the process by minimizing the noise contained in the ECG signal and being able to separate the noise. The result of preprocessed signal can be seen in Fig. 4.

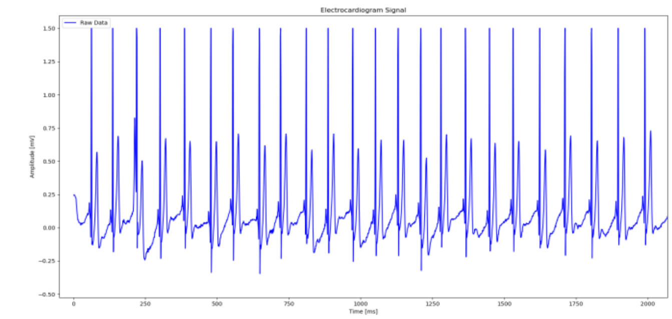

Fig. 3. Heart Rate Signal Recording using Portable ECG devices.

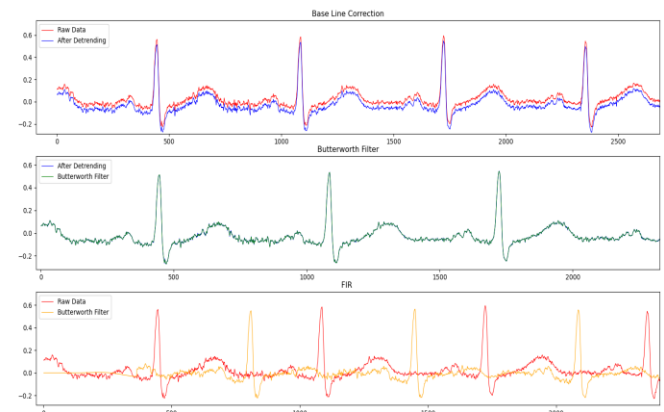

Fig. 4. One of the results of the preprocessed ECG signal.

When the pre-processing has been completed, feature extraction will be performed on the filtered data to obtain the PQRST value of the heart wave and then classify the possibility of abnormalities based on the PQRST interval obtained data. An example of the results of reading the PQRST value from a heart signal using a Butterworth filter that has been tested can be seen in Fig. 5.

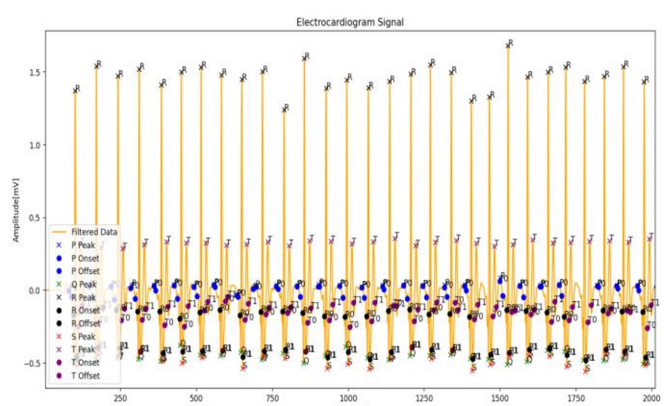

Fig. 5. ECG signal after filter and PQRST Detection.

The ANN model was made using target labels with values 0 and 1. Value 0 is the result of Normal detection and 1 is the result of Arrhythmia detection. The dataset that used are 221 data from normal and Arrhythmias dataset that collected from the experiments and physiobank website. The raw signal that have been processed was made into data frame in excel to be cleaned from any missing values and outliers. Then the classification process can be started. Before the model built, the data will be going through an normalization using minmax scaling to change the data so that the length of the feature vector is 1 Euclidean. After that the data was divided into training and validation data with 90%:10% scale. For the ANN model there are several layers used in the model building process, there are exactly 8 Hidden Layers with the number of nodes varying from 512 nodes down to 32 nodes. The activation functions that are used are all ReLU and the last one is sigmoid. After the architecture is completed the model goes through training iterations to get the highest possible accuracy. Then after going through 103 training iterations, the model showed significant accuracy results. The results of the ANN model training can be seen in Fig. 6 and 7.

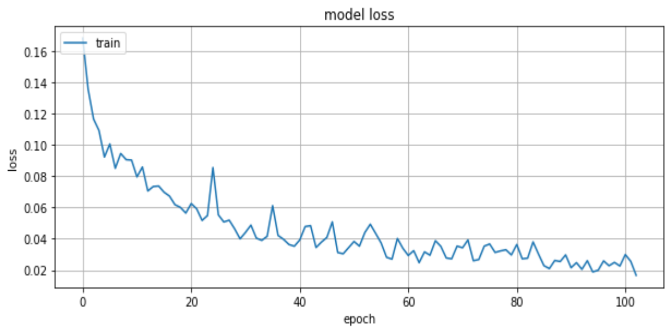

Fig. 6. Training-Loss Graph of the ANN Model.

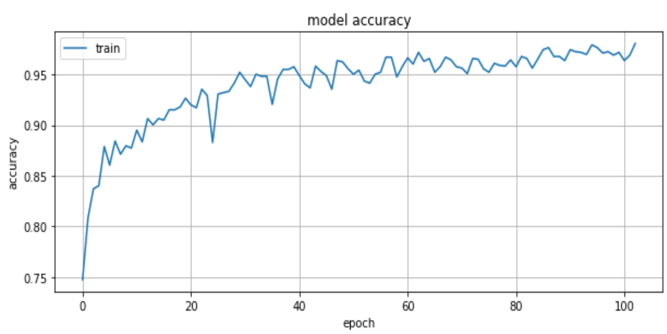

Fig. 7. Training-Accuracy of the ANN Model.

After the training was completed, we evaluate the model using one of python function to check the accuracy and we got 94,12% accuracy. To evaluate the model, we used the data we used on training, because we already know the label from each of the data.

The Table 1 shows 10 out of the existing trial validation data as part of the results. To check the results of the model, we made a program to check if the predictions were right using the 20s data from the validation dataset that was already split earlier before we trained the model. The first column (True_Val) is the original classification value and the second column (Predicted_Val) is the predicted value of the model that has been built with an accuracy of 94.12%. As shown in the Table I, there are two wrong predictions out of 10 results that show the model is good enough to perform a classification and can differentiate the normal and possible arrhythmias.

To check the model's performance, we evaluated the model using all of the 220 trial data to validate the model predictions, and out of 220 data predicted, there were 13 wrong predictions. Based on the existing validation, validation precision in making predictions can be calculated using the equation:

$$Precision = \frac{Total\ data - Total\ Wrong\ Prediction}{Total\ data}$$

$$Precision = \frac{220-13}{220} = 94{,}09\%$$

For another type of performance evaluation, we used the confusion matrix to measure the accuracy, precision, recall, and F-1 score using a validation dataset that have been divided earlier before we trained the model. The confusion matrix can be seen on Table 2.

Table 2 containing the data validation set for the model, using only 20 data that have been parted earlier for model validation accuracy where it contains 10 True Positive, 9 True Negative, 3 False Positive, and 3 True Negative. From Table 2 we can see the confusion matrix measurement of the ANN model that have been made. The accuracy, precision, recall or sensitivity, and F-1 Score value, then calculated using equations (2-6) with the results as: 82.6 %, 90.9%, 76.9%, and 83.3%, respectively.

TABLE I
PREDICTION RESULTS

True_Val	Predicted_Val	Validation
0	1	Wrong
0	0	Right
0	1	Wrong
0	0	Right
0	0	Right
0	0	Right
0	0	Right
0	0	Right
0	0	Right

TABLE II
CONFUSION MATRIX AFTER THE CLASSIFICATION PROC

Value	True	False
Positive	10	1
Negative	9	3

IV. CONCLUSIONS

Based on the results of tests carried out on the classification model using an artificial neural network or ANN, it can be concluded that the classification model that has been made can be used and functions properly. The ANN model used in the training has an accuracy validation of 94.12% with a model precision of 90.9% and successfully classifies the possible disease according to its class.

Some suggestions for improving this research are that the ECG module sensor can be replaced with a sensor that has a higher sensitivity. Then it can be re-designed a better network architecture with other methods or fix the deficiencies of the model by adding more appropriate layers and hyperparameters to get higher accuracy results.

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